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# Assessment of climate extremes in future projections downscaled by multiple statistical downscaling methods over Pakistan

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A R T I C L E I N F O

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A B S T R A C T

Climate change is a phenomenon that is unequivocally altering the natural systems in all parts of the world but the alteration in climate extremes may pose more severe and unexpected impacts on Pakistan. The current study provides a comprehensive outlook of observation (1976–2005) and changes in climate extremes between the reference (1976–2005) and future periods (2020s: 2006–2035, 2050s: 2036–2065 and 2080s: 2066–2095). The analysis was conducted across six sub-regions of Pakistan including North Pakistan (NP), Monsoon Region (MR), Khyber Pakhtunkhwa (KP), Southern Punjab (SP), Balochistan and Sindh for which Coupled Model Intercomparison Project Phase 5 (CMIP5) 14 General Circulation Models (GCMs) under Representative Concentration Pathways 4.5 (RCP4.5) and RCP8.5 were downscaled and bias corrected by three statistical downscaling methods. The spatial disaggregation and quantile delta mapping (SDQDM) method was used for future projections in this study. Changes in climate extremes were detected by Expert Team on Climate Change Detection and Indices (ETCCDI). In case of temperature, the results indicate a projected increase in frequencies and magnitudes for warm extremes, while it is decreasing for cold extremes in the 21st century. The corresponding trends of maximum and minimum temperature extremes are greater than the mean temperature trend; where the frequency and magnitude of minimum temperature extremes is higher than maximum temperature extremes over Pakistan particularly over North in last half of the 21st century for both RCPs. Also, the average of temperature extremes (TXx, TXn, TNx and TNn) are severe in the order of NP (+4.8 °C), KP (+4.6 °C) and MR (+4.5 °C). In the case of precipitation extremes, most of the sub-regions across Pakistan show a higher increase in total annual precipitation and intense precipitation events with the highest increase in MR, KP and NP and the least increase in Sindh. Despite the increase in total precipitation, numbers of consecutive dry days (CDD) are increasing while consecutive wet days (CWD) are decreasing which can give rise to drought conditions particularly in Sindh. The study provides complementary and consistent climate extremes information over Pakistan for local decision makers to incorporate into policy-making, disaster management, and infrastructure planning.

## 1. Introduction

Over the last decades, the frequency, magnitude and duration of extreme events have increased, which is likely to exacerbate in future with an increase in anthropogenic activities (Intergovernmental Panel on Climate Change (IPCC), 2013). The occurrence of extreme events is not uniform across the globe where some regions are more sensitive to changing climate extremes than others. Pakistan, in particular, has been

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frequently hit hard by intense floods and heat waves in the past half-decade (Rasmussen et al., 2015; Iqbal et al., 2018; Masood et al., 2015; Nasim et al., 2018; Depeng et al., 2018; Fahad et al., 2017; Fahad et al., 2016a, 2016b, 2016c, 2016d; Fahad et al., 2015a, 2015b; Fahad et al., 2018; Ghulam et al., 2017; Hafiz et al., 2018; Ihtisham et al., 2018; Muhammad et al., 2017; Muhammad et al., 2018; Yang et al., 2017). Therefore, information on future extreme climate changes in Pakistan is urgently required to develop timely and effective adaptation strategies and policies. The projections of climate models provide fundamental information relevant to policy- makers. However, their efficiency to project the present and future climatology has been debated mainly due to large uncertainties arising during the formal verification and validation processes. To establish the confidence on climate models by policy-makers, the scientific community has been targeted to improve the performance of climate models and to select better models by inter-comparison, e.g., coupled models inter-comparison project. Generally, no single GCM performs well to simulate all the processes of the atmospheric system and shows wide-spread variations in climate conditions at a finer scale. In other words, some models simulate one process well (e.g. ENSO) whereas poorly simulating the other processes (e.g., monsoon). Also, GCMs are passive to resolve the complex topography of mountains (with sudden changes in elevation) and are unable to provide accurate climatic information at finer local scale due to coarse horizontal resolutions and systematic biases (Fu et al., 2008; Sillmann et al., 2013a). There is a mismatch of spatial resolution between GCMs and impact studies models. Therefore, downscaling techniques are essential to minimize the gap at local or regional scales (e.g., Wood et al., 2002; Wilby and Wigley, 2000).

Downscaling is a process to produce finer scale information from the coarse scale. There are two fundamental approaches of downscaling: dynamical downscaling (DD) and statistical downscaling (SD). Dynamic downscaling employs regional climate models at finer-scales (10–50 km) to simulate local meteorological processes by incorporating regional features such as topography. Though DD is an emerging field and the method mostly used is by nesting GCMs to Regional Climate Models (RCMs), (Leung et al., 2004; Giorgi and Mearns, 1991; Yarnal et al., 2000), however, these have the limitations of high computational requirements, data storage (especially in multiple realizations of an experiment) and cascade-biases from GCMs to RCMs (Wood et al., 2004). On the contrary, statistical downscaling (SD) is efficient and easy to apply, which directly incorporates the relationship between observation and GCM's output (Fowler et al., 2007). Therefore, statistical bias correction/downscaling algorithms have been actively developed by the scientific community to produce climate projections at the local scale necessary for impact studies, e.g. crop and hydrology simulations (Wood et al., 2002, 2004; Gudmundsson et al., 2012; Hundecha et al., 2016; Sunyer et al., 2015; Su et al., 2016; Li Liu et al., 2017). However, it has potentially serious problems of statistical stationarity (Wilby et al., 2004). There are several statistical bias correction methods, e.g. BCSD (Wood et al., 2002, 2004) that are often applied to climate model data for both 1) bias correction and 2) downscaling to a finer target resolution from a coarse one. Bias-correction is usually carried out to adjust variance, mean and higher moments of distribution by parametric (Piani et al., 2010; Eum et al., 2010) and non-parametric quantile mapping techniques (Gudmundsson et al., 2012). However, there are many issues associated with it; for example, corrupt GCM-driven climate change signals in future projections. Some studies have applied improved bias correction techniques to preserve the climate change signals in climate models (Taylor et al., 2012; Hempel et al., 2013; Bürger et al., 2013). However, these studies have limitations that may alter trends in daily data and precipitation extremes. To overcome this problem, Detrended Quantile Mapping (DQM) was used with preserved modeled trends by superimposing modified historical observations (Willems and Vrac, 2011; Sunyer et al., 2015). However, DQM does not guarantee to preserve relative changes in mean as it displaces precipitation features in complex terrain and is unable to bias-correct daily data directly from GCMs (Maraun and Widmann, 2015). The majority of statistical downscaling methods for climate projections have paid attention to how the changes in mean values can reflect in newly downscaled climate datasets, e.g., detrented quantile mapping. As they can preserve the mean change but not extreme values. New methods have been suggested to properly reflect changes in extreme values (Cannon et al., 2015; Shashikanth et al., 2017). In this study, we present the results of Quantile Delta Mapping (QDM: Cannon et al., 2015; Eum and Cannon, 2016) which preserves climate change signal (trend) in simulated quantiles from GCMs and overcome the problems of DQM.

Changes in temperature and precipitation extremes at global scale were first reported in the Third Assessment Report (*The Third Assessment Report of the Intergovernmental Panel on Climate Change*, n.d.). Frich et al. (2002); Many studies assessed global picture of observed climate extremes (Alexander et al., 2006; Donat et al., 2013), which significantly contributed to Assessment Reports (AR3-AR5) (Alexander, 2016) Changes in climate extremes based on indices were also analyzed by many researchers (e.g. Tebaldi et al., 2006; Kharin et al., 2007; Alexander and Arblaster, 2009; Russo and Sterl, 2011; Sillmann et al., 2013a, 2013b). Revadekar et al. (2011) and Sheikh et al. (2015a, b) indicated increasing trend of warm temperature extremes over South Asia while precipitation extremes show mixed trend. Other regions of South Asia (e.g. India) have also shown inclination towards warmer climate which is facing more rapid and sharp increase in minimum, surface temperature, extreme heat and cold events (Kothawale and Rupa Kumar, 2005).

There are several studies on climate extremes over Pakistan but exist limitations in the methodologies and datasets. Shashikanth et al. (2014) analyzed observed temperature and precipitation extremes from 1960 to 1990 but the study does not provide future projections of these extremes. A study conducted by Ul Islam et al. (2009) utilized only one RCM without taking into account any bias correction method. However, Mahmood and Babel (2014) used simple bias correction for baseline period and adjusted it for future but the limitation of the study lies in the fact that the bias correction method used in the study does not preserve long term trends in future. Also, the study area covers only a small basin in Pakistan. Sajjad and Ghaffar (2018) analyzed climate extremes based on bias corrected data over whole country but the datasets used in the study is based only on 3 GCMs from NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) and also have stationarity in data. All the previous studies also have suffered from the assumption of stationarity in the relationship between observation and climate projections. This study overcomes the limitations posed by previous studies conducted with same theme over Pakistan as QDM provides bias-correction as it fits into the marginal distribution of observations along with considering the changes in all quantiles between the reference and future periods. In this study, Cumulative Distribution Function (CDF) for a future period was built with 30-year future time window. For example, the CDF in 2050 is formulated with climate data from 2035 to 2064. In this way, the changes in all quantiles can be evaluated by CDFs for the reference and future over time to consider the non-stationarity in each climate variable. Therefore, this is one of the most comprehensive study which provides deep insight into future extreme events over Pakistan. The findings of this study enables the policy makers to evaluate the impacts of changing climatic extremes on terrestrial and aquatic systems which can contribute in decision making process to devise adaptation strategies for extreme phenomenon like floods, heatwaves, and drought.

This paper aims to provide future projection of climatic extremes for 21st century from statistically downscale 14 multi-GCMs ensemble projections with emission scenarios of RCP 4.5 and RCP 8.5 over Pakistan. It also compares the trends in observed (1976–2005) and models simulated extreme, uncertainty in the projected climatic extremes and limitation of the study. In addition, the study inter-compares the performance of multiple statistical downscaling/bias-correction methods i.e. Quantile Mapping (QM), Detrended Quantile Mapping (DQM) and Quantile Delta Mapping (QDM).


**Fig. 1.** Location of meteorological stations (black circles), Rivers (blue lines) and the Tarbela dam (triangle blue) along with sub-regions (North Pakistan (NP), Monsoon Region (MR), Khyber Pakhtunkhwa (KP), Southern Punjab (SP), Balochistan and Sindh), neighbors and topography. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

## 2. Methodology

In this section, we describe the characteristics of the study area, data sets and their sources of acquisition; and methods of executing various procedures to achieve the objectives of the study.

### 2.1. Study area

Pakistan is blessed with diverse landscapes having hills, forests, deserts to plains and plateaus. It stretches from the south of coastal areas of the Arabian Sea to the north of Karakoram and Himalaya mountains and lies between 23.5°–40°N and 60°–80°E in the temperate zone of sub-tropics. The northern region of Pakistan is the part of third largest glacier/snow reservoirs called the third pole to contain > 5000 glaciers and the world second highest mountain peak K2 (Fig. 1).

Pakistan has wide variations in temporal and spatial climatology and weather condition in different regions of hot desert, humid coast and icy mountains. Pakistan experiences four seasons around a year: summer monsoon from July–September which contributes 60% of total annual rainfalls, pre-monsoon from May–June (hot and dry), post-monsoon from September–October and winter from November to February (cold and dry). Summer season is humid and extremely hot where the humidity is 25–50% and temperature reaches 49 °C and more in plain areas. Winter season is cold and average temperature ranges between 4 °C to 20 °C in most of the areas. In Northern regions of the country; the temperature falls below freezing point. The mean temperature in Pakistan has increased over 0.6 °C during the 20th century which is in agreement with IPCC findings. The increase was higher in northern parts (0.8 °C) as compared to southern parts (0.6 °C) during 1900–2000. Further, it was higher in the second half compared to the first half of the last century (GCISC et al., 2009).

The precipitation pattern in different parts of Pakistan is mostly affected by the monsoon winds and the western disturbances and differs on varied ranges. The rainfall is generally divided into two spells (i.e. winter and summer or monsoon). Khyber Pakhtunkhwa, northern mountains region and some part of Balochistan receive precipitation in Dec-March while in July–September Punjab and Sindh receive maximum rainfall of about 50–75%. Meteorological stations data show an increasing trend in annual precipitation by 25%, especially in monsoon dominated regions. However, this increase is not consistent with the 1994–2000 decreasing trend (GCISC et al., 2009). At the Himalayan region (above 35°N), solid raifall (i.e., snow) occurs during winter, and monsoon region receives more rainfall in summer while Sindh coastal and some part of Balochistan receive less rainfall. All these changes in precipitation and temperature are the important parameters for agriculture and water resources, particularly in mountainous regions of

**Table 1**
14 Global climate model (GCMs) of CMIP5 downscaled in this study.

| | | | |
|---|---|---|---|
| 1 | CanESM2 | 2.7906 × 2.8125 | Canadian Centre for Climate Modelling and Analysis |
| 2 | CCSM4 | 1.250 × 0.942 | National Center for Atmospheric Research |
| 3 | CESM1-CAM5 | 1.250 × 0.942 | National Center for Atmospheric Research |
| 4 | CMCC-CMS | 1.875 × 1.865 | Centro Euro-Mediterraneo per I CambiamentiClimatici |
| 5 | CNRM-CM5 | 1.406 × 1.401 | Centre National de RecherchesMeteorologiques |
| 6 | EC-EARTH | 1.1215 × 1.125 | Irish Centre for High-End Computing (ICHEC), European Consortium |
| 7 | FGOALS-s2 | 2.813 × 1.659 | LASG, Institute of Atmospheric Physics, Chinese Academy of Sciences |
| 8 | GFDL-ESM2G | 2.500 × 2.023 | Geophysical Fluid Dynamics Laboratory |
| 9 | GFDL-ESM2M | 2.500 × 2.023 | Geophysical Fluid Dynamics Laboratory |
| 10 | INM-CM4 | 2.000 × 1.500 | Institute for Numerical Mathematics |
| 11 | MIROC-ESM-CHEM | 2.7906 × 2.8125 | National Institute for Environmental Studies, The University of Tokyo |
| 12 | MPI-ESM-LR | 1.875 × 1.865 | Max Planck Institute for Meteorology (MPI-M) |
| 13 | MPI-ESM-MR | 1.875 × 1.865 | Max Planck Institute for Meteorology (MPI-M) |
| 14 | NorESM1-M | 2.500 × 1.895 | Norwegian Climate Centre |

northern Pakistan.

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### 2.2. Data

Globally, CMIP5 models represent climatic extremes trends reasonably well (Sillmann et al., 2013a). In this study, 14 CMIP5 GCMs (Table 1.) were selected based on the results of our initial findings and availability of data for the variables i.e. precipitation, maximum temperature and minimum temperature from http://cmip-pcmdi.llnl.gov/cmip5/data_portal.html for 21st Century. This data is used for model evaluation, statistical downscaling and future projection of climatic extremes.

Maximum temperature, minimum temperature, and precipitation daily data of observed meteorological stations for the duration of 1976–2005 were acquired from Pakistan Meteorological Department (PMD) with few missing values. The missing values were replaced using statistical imputation (Jakobsen et al., 2017). Multiple chains have been run and the convergence was assessed after performing a specified number of iterations in each chain. The optimized values were used after some iteration when there was no improvement observed in the imputed values. This dataset is used for the observed climatic extreme trends, evaluation of the historical extremes in the models mean for the period of 1976–2005 and for statistical downscaling/bias correction of GCMs' temperature and precipitation for the period of 1976–2095.

### 2.3. Analysis and ensemble application

The climatic extremes events were analyzed from the observed data of PMD from 1976 to 2005 and evaluation of 14 GCMs using ClimPACT2 (Alexander and Herold, 2015). CMIP5 GCMs data is extracted over the South Asian domain of temperature and precipitation for the period 1976–2005 and 2006–2095. The GCMs data was statistically downscaled/bias-corrected using spatial disaggregation quantile mapping (SDQM), spatial disaggregation detrended quantile mapping (SDDQM) and spatial disaggregation quantile delta mapping (SDQDM) (Cannon et al., 2015; Eum and Cannon, 2016) at 34 observed meteorological stations over Pakistan. The climate models' output data is based on future scenarios of RCP4.5 (Clarke et al., 2007) with 4.5 W/m$^2$ and RCP8.5 (Riahi et al., 2007) with 8.5 W/m$^2$radioactive forcing by 2100.

The results were prepared to carry out detailed analyses for the whole Pakistan divided into different six regions (North Pakistan, Monsoon Region, Khyber Pakhtunkhwa, Southern Punjab, Balochistan and Sindh) according to the climatology of the regions (Sheikh et al., 2009) and provincial boundary (Fig. 1). We used extreme indices for temperature and precipitation recommended and developed by the Expert Team on Climate Change Detection, Monitoring and Indices (ETCCDI – Table 2) in collaboration with the World Meteorological Organization (WMO). The uncertainties in projection also analyzed using Probability Density Functions (PDFs), Box whiskers plots and

**Table 2**
Expert Team on Climate Change Detection and Indices (ETCCDI) employed in this study.

| Index | Description | Unit |
|---|---|---|
| SU | Annual count of days when TMAX > 25 °C | Days |
| ID | Annual count of days when TMAX < 0 °C | Days |
| TXn | Annual minimum value of TMAX | °C |
| TXx | Annual maximum value of TMAX | °C |
| TX10p | Percentage of days when TMAX < 10th Percentile | % |
| TX90p | Percentage of days when TMAX > 90th percentile | % |
| WSDI | Annual count of days with at least 6 consecutive days when TMAX > 90th percentile | Days |
| FD | Annual count of days when TMIN < 0 | °C Days |
| TR | Annual count of days when TMIN > 20 | °C Days |
| TNn | Annual minimum value of TMIN | °C |
| TNx | Annual maximum value of TMIN | °C |
| TN10p | Percentage of days when TMIN < 10th percentile | % |
| TN90p | Percentage of days when TMIN > 90th percentile | % |
| CSDI | Annual count of days with at least 6 consecutive days when TMIN < 10th percentile | Days |
| DTR | Annual mean difference between daily TMAX and TMIN | °C |
| GSL | Number of days between the first spells of warm and cold days | Days |
| CDD | Maximum number of consecutive days with daily PRCP < 1 mm | Days |
| CWD | Maximum number of consecutive days with daily PRCP ≥1 mm | Days |
| PRCPTOT | Annual total PRCP in wet days (daily PRCP ≥1 mm) | mm |
| Rx1day | Annual maximum 1-day precipitation | mm |
| Rx5day | Annual maximum 5-day precipitation (PRCP) | mm |
| R95pTOT | Annual total PRCP when daily PRCP > 95 percentile | mm |
| SDII | Annual precipitation divided by the number of wet days | mm/day |

Signal to Noise Ratio (SNR).

#### 2.3.1. Quantile mapping (QM) method

According to Woodcock et al.(2004), QM linear method is better performing method as compared to others. QM equates cumulative distribution functions (CDFs) and is represented mathematically as below:

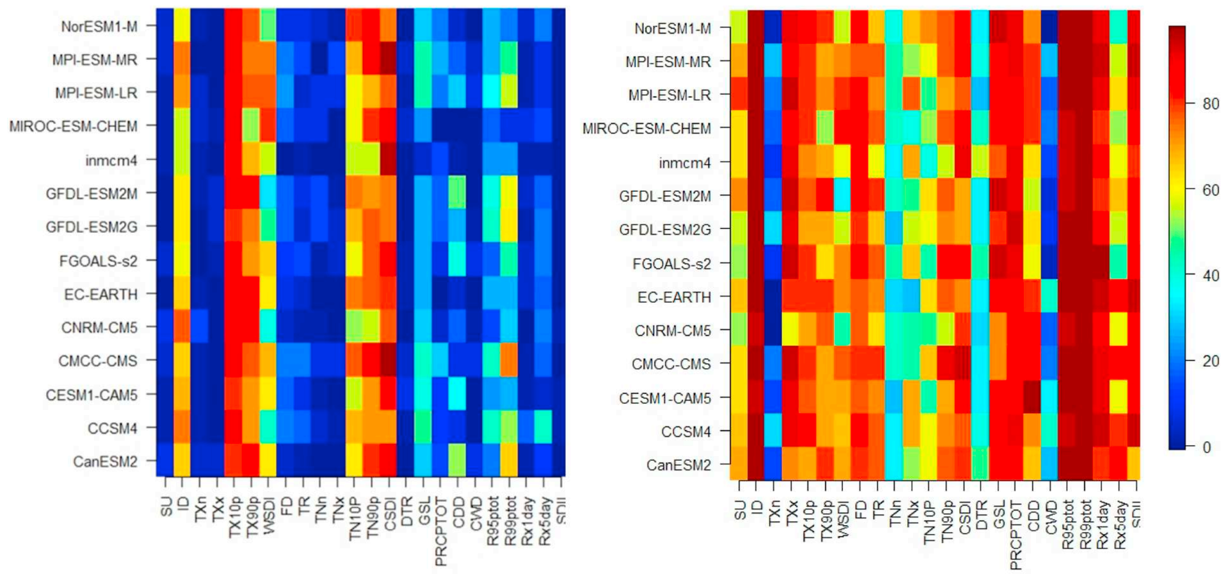
The three steps methodology of quantile mapping bias correction starts with building cumulative distribution function (CDF) of model output. Secondly, it involves calculation of the distribution function of observed historical data and implementation of the inverse of this function to the distribution function of model output data given in (Eq. (1)–(3)).

$$\rho_m = F_m(x_m) \tag{1}$$

$$\rho_o = F_o(x_o) \tag{2}$$

$$\tilde{x}_m = \rho_o^{-1}(\rho_m) \tag{3}$$

where $\tilde{x}$, $x_m$ are bias corrected and original model outputs, $F_m$, $F_o^{-1}$are




(a) Simple spatial interpolation

(b) Simple spatial interpolation with Bais corection

**Fig. 2.** Performance of K–S test by simple spatial interpolation and Simple spatial interpolation with Bais correction for extreme climate indices.

the CDF of simulated data and the inverse of CDF for observed climate data, respectively.

According to Cannon et al. (2015), QM bias-correction relies on the assumption that the features of historical data is stationary and will persist into the future period data.

#### 2.3.2. Detrended qauntile mapping (DQM) method

We start with the ratio of long-term average values of model's predicted data in future to the baseline period.

$$R_{f,h} = \frac{\bar{x}_{m,f}}{\bar{x}_{m,h}} \tag{4}$$

Then the cumulative distribution function of the ratio of average values of model's simulated data in the baseline period to future period multiplied with model's predicted data in the future was computed.

$$\rho_{m,h} = F_{m,h}\left\{\left(\frac{\bar{x}_{m,h}}{\bar{x}_{m,f}}\right). x_{m,f}(t)\right\} \tag{5}$$

Finally, the cumulative distribution function of observed historical data was implemented to the CDF of model's predicted historical data multiplied with ratio calculated in Eq. (4).

$$\tilde{x}_{m,f}(t) = F(x_{o,h})^{-1}[\rho_{m,h}.\ R_{f,h}] \tag{6}$$

For temperature, the same procedure can be repeated but it is required to add the difference between model's future and baseline data instead of multiplications.

$$D_{f,h} = \bar{x}_{m,f} - \bar{x}_{m,h} \tag{7}$$

$$\rho_{m,h} = \{x_{m,f} + (\bar{x}_{m,h} - \bar{x}_{m,f})\} \tag{8}$$

$$\tilde{x}_{m,f}(t) = \rho_{o,h}^{-1}[\rho_{m,h} + (\bar{x}_{m,f} - \bar{x}_{m,h})] \tag{9}$$

#### 2.3.3. Quantile delta mapping (QDM) method

It is assumed that $x_o$,$x_{m,\ h}$,$x_{m,\ p}$ denote observed, model's simulated historical and future data, respectively. Similarly, $\rho_{o,\ h}$, $\rho_{m,\ h}$, $\rho_{m,\ f}$ represent the CDFs of historical observed data, model's simulated data for historical time and future time period, respectively. We started with time dependent cumulative distribution function of model projected series$x_{m,\ f}$. method. Further, $x$ and ρ represent data and CDF of the data, respectively.

$$\rho_{m,f}(t) = F_{m,f}(t)(x_{m,f}(t)),\ \rho_{m,f}(t) \in [0,1] \tag{10}$$

Find the relative change using the ratio of inverse CDF of model predicted data applied to the CDF of model predicted data and the inverse CDF of observed historical data applied to model predicted data. Mathematically this can be represented by equation

$$\Delta_m(t) = \frac{F^{(t)}{}_{m,f}{}^{-1}(\rho_{m,f}(t))}{F_{m,h}{}^{-1}(\rho_{m,f}(t))} = \frac{x_{m,f}(t)}{F_{m,h}{}^{-1}(\rho_{m,f}(t))} \tag{11}$$

The quantile of model's predicted data $\rho_{m,\ f}(t)$ can now be bias corrected by applying the inverse CDF estimated from historical observed data.

$$\tilde{x}_{o,m}(t) = F_{o,h}{}^{-1}(\rho_{m,f}(t)) \tag{12}$$

The bias-corrected future projections can be obtained by applying the relative changes to the historical bias-corrected data given in Eq. (12).

$$\tilde{x}_{m,f}(t) = \hat{x}_{o,m}(t) + \Delta_m(t) \tag{13}$$

$\tilde{x}_{m,f}(t)$is the future model's bias corrected data and can be used for further analysis. To preserve relative changes in the data, Eqs. (11) and (12) can be applied multiplicatively rather than additively (Cannon et al., 2015).

## 3. Results and discussion

The frequency and magnitude of extreme events vary with different regions, seasons and types of extreme events. The analysis of different indices of temperature and precipitation for observed (1976–2005) and statistically downscaled model data of 14 GCMs (2006–2095) are presented in this section. Firstly, the result of Kolmogorov–Smirnov (K–S) test is exhibited to check the performance of downscaled bias-corrected data. The results of observed, model's historical and future climatic extremes over whole of Pakistan are demonstrated for both RCP4.5 and RCP8.5 while for six (6) sub-regions (provinces) the results shown are


**Fig. 3.** Validation trends of time series of observed (blue) and models under ensemble mean (red) of temperature extremes over different regions of Pakistan from 1976 to 2005. Straight lines represent linear regressions. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

only for RCP8.5.

Fig. 2 shows the passing ratio of K–S test for 34 stations in Pakistan for the simple spatial interpolation and simple spatial interpolation along with bias correction. It is noted that performance of K–S test for temperature is better than for precipitation. Moreover, it is evident that statistical downscaling methods have significantly improved the performance for majority of indices over Pakistan, especially for high resolution models, e.g., EC-EARTH, CCSM4, CMCC-CMS and MPI-ESM-MR. However, all the models have shown passive performance for minimum of maximum temperature (TXn), minimum of minimum temperature (TNn) and consecutive wet days (CWD) even after the implementation of statistical bias correction techniques. This might happened due to variations in data that arise after replacing missing values at some stations.

### 3.1. Changes in temperature extremes

Fig. 3 demonstrates some of the observe and models ensemble trends for temperature extremes from 1976 to 2005 over different regions of Pakistan. Most models ensemble mean represent climatic extremes trends reasonably well close agreement with observed trends. However, the uncertainties exist for some indices on different regions which is also reported by Sillmann et al. (2013a) for CMIP5 globally. For instance, cool nights and days are observed to decrease while warm nights and days have increased that are in consistent with models trend. However, consensus between observe and models ensemble mean specially over some stations of NP is weak e.g. in Gupis observed cool nights have increased but model mean is showing decreasing trend may be due to coarse models resolutions and complex topography. These contrast results are consistent with study of Forsythe et al. (2017) suggests that there are deviations from general pattern of warming over the Karakoram and even summer cooling is seen that give general response to the Karakoram Anomaly. Also, the warm spells over Balakot has shown a decreased observed trend but it is increasing in model trend. In Lahore and Parachinar, a slight difference between observed and models trend exist for warm nights and days as well. With respect to temperature change, the observed average temperature over Pakistan has increased to 0.5 °C with increase in maximum temperature upto 0.8 °C which is consistent with the finding of Burhan and Shahid (2017) and Sajjad et al., (2018). However, the highest increase in minimum temperature is observed to be 0.79 °C which was witnessed over Southern Punjab while Balochistan experienced highest increase in maximum temperature of 1.38 °C. It was observed that all the warm temperature extremes have shown an increasing trend in all the stations while cold temperature extremes have decreased except for few stations such as regions in NP, Murree and Parachinar where cool nights (TN10p) has increased.

A comparison of trend preserving capacity of QM, DQM and QDM for future projection of extremes are presented along with the model trend in Fig. 4. It can be noted that the performance of QDM dominates other methods in performance and can be considered as a reliable method of bias correction for future projection studies as other two methods (QM and DQM) encounter the problem of stationarity. Hereafter, due to least biases, non-stationarity and trend preserving capability, the results of QDM only are presented in the study.

For future projection of temperature, the related indices are divided into two groups based on the unit of each index in Fig. 5 i.e., the upper panel represents temperature in Celsius (°C) unit and the lower pannel displays units of percentages and days. Also, theses relative changes in temperature extremes are presented for RCP 4.5 and RCP 8.5 across Pakistan. The frequency and magnitude for warm extremes (i.e., TR, TX90, TN90p, TXx, TXn, TNx, TNn, SU and GSL) are increasing which are likely to occur more often in the future, while it is decreasing for cold extremes (i.e. FD, TN10p, TX10p, ID, and CSDI) in the 21st century. As indicated by Intergovernmental Panel on Climate Change (IPCC), 2013 and Sillmann et al. (2013b), these results are in agreement with the global scenario for temperature extremes. Under RCP 8.5, the temperature is projected to increase by 1.2 °C in the 2020s, 2.5 °C in 2050s and 4.5 °C in 2080s. This increase in temperature is higher for minimum temperature and cause a decrease in daily temperature range (DTR). While for RCP 4.5, the rise in temperature is projected to be 0.8 °C in 2020s, 1.5 °C in 2050s and 2.2 °C in 2080s. Under this scenario, the increase in the maximum of both maximum and minimum temperature are approximately the same, so there is no decrease in DTR. However, the magnitude differs from temporal and spatial. However, the increase in a minimum of minimum (TNn) temperature is higher than the minimum of maximum (TXn) temperature in the last two halves. Hence, minimum temperature (TNx, TNn) change is at a rate greater than that of the maximum temperature (TXx, TXn) which indicates a strong contribution of the minimum temperature to the overall temperature increases. In general, the higher warming trends for minimum temperature than maximum temperature are predominantly consistent with the finding of Alexander and Arblaster (2009).

For the sub-regions of Pakistan, the results are presented only for RCP8.5 in Figs. 6 and 7. The temperature extremes are severe in North Pakistan (4.8 °C increase), KPK (4.6 °C increase) and Monsoon region (4.5 °C increase) and which makes Northern Pakistan one of the most vulnerable area to global temperature change. Such result may be a threating point to glacier melting, monsoon spell, and flash flood, etc. The overall alarming results for NP obtained from our study are consistent with the results of Krishnan et al. (2019) state that Hindu Kush Himalaya (HKH) will observe higher warming of 0.3–0.7 °C, if the increase in global average temperature is retained to 1.5 °C and the projected temperature change is 2.5 ± 1.5 °C for RCP4.5 and 5.5 ± 1.5 °C for RCP8.5 by the end of the 21st century. The higher level of warming for 21st Century over NP also in correspondence with the finding of Rehman et al., 2018which show more increase in temperature over Pakistan than global average and increase is higher over northern side, which will make the climatic extremes events more frequent over NP and authenticate the claim Pakistan variability to climate change. The increase in minimum temperature extremes is higher in North Pakistan and Monsoon region (with 2 °C difference from each other) than the southern part. DTR indicates the mean difference between TXx (the maximum temperature) and TNn (the minimum temperature), therefore a decrease in DTR is seen in most of the stations, while the rate of increase of TNn (0.47 °C per decade) was greater than that of TXx (0.22 °C per decade)., DTR is dependent on minimum temperature, so it decreases where there is a high increase in minimum temperature. The increasing trend in temperature is also reported by Ali et al. (2015) which shows the increase in minimum temperature is larger in both scenarios for all future periods in this region. Summer days (SU) are increasing in all the regions with the highest increase in KP and MR of 70 days. Apart from Sindh and Southern Punjab where there exist no FD and ID, all other regions show a significant decrease in FD where the highest decrease is shown by north Pakistan followed by monsoon and KP while ID is also decreasing in all parts. Growing season length (GSL) depicts an increase in NP, KP, MR and Balochistan, while no significant change can be seen in Southern Punjab and Sindh. The GSL indicates a significant increasing trend of 15–50 days in NP which is an important factor for plants growth. The growing season prolongs in the areas of higher elevation due to warming in these areas. Our results also show the high increase in observed maximum temperature which might be the cause of increasing trend in GSL over high elevation. The lower temperatures act as constraint on plants growth, whereas higher temperature accelerates the vegetation maturation at lower elevations, potentially leading to a shorter growing season in some low-elevation areas. The similar findings of elevations dependent GSL are also reported by Wang et al. (2018) over China which is getting prolong over higher-elevation and shorten at low-elevation. Moreover, tropical nights (TR) is also increasing at the highest rate in the Monsoon region, followed by KP and NP. During the 2020 period, the highest increase in tropical nights (TR) of 20 days is seen over Sindh and Balochistan while the other regions possess a 15-day increase. In MR and KP, an overall increase of 60 days in TR was observed. Cool nights (TN10p) and days (TX10p) show a decreasing trend, while warm nights (TN90p) and days (TX90p) are increasing in all the sub-regions. Sindh displays the highest increase in TN90p and TX90p of 75 and 60 days respectively. In NP, the increase in TN90p is high (i.e. 70 days) as compared to TX90p which is of 50 days. This provides an indication that the warming of night temperatures (TN90) has greater contribution to the overall warming trend as compared to the warming of day temperatures (TX90). Similarly, MR, KP and SP are also observed to have more increase in TN90p as compared to TX90p. However, Balochistan possesses the same increase of 60 days in both TX90p and TN90p. An increasing trend of Warm spell duration index (WSDI) is observed in all the sub regions with the highest increase of 210 days being observed in SP. In MR and Sindh, the resultant trends of WSDI are

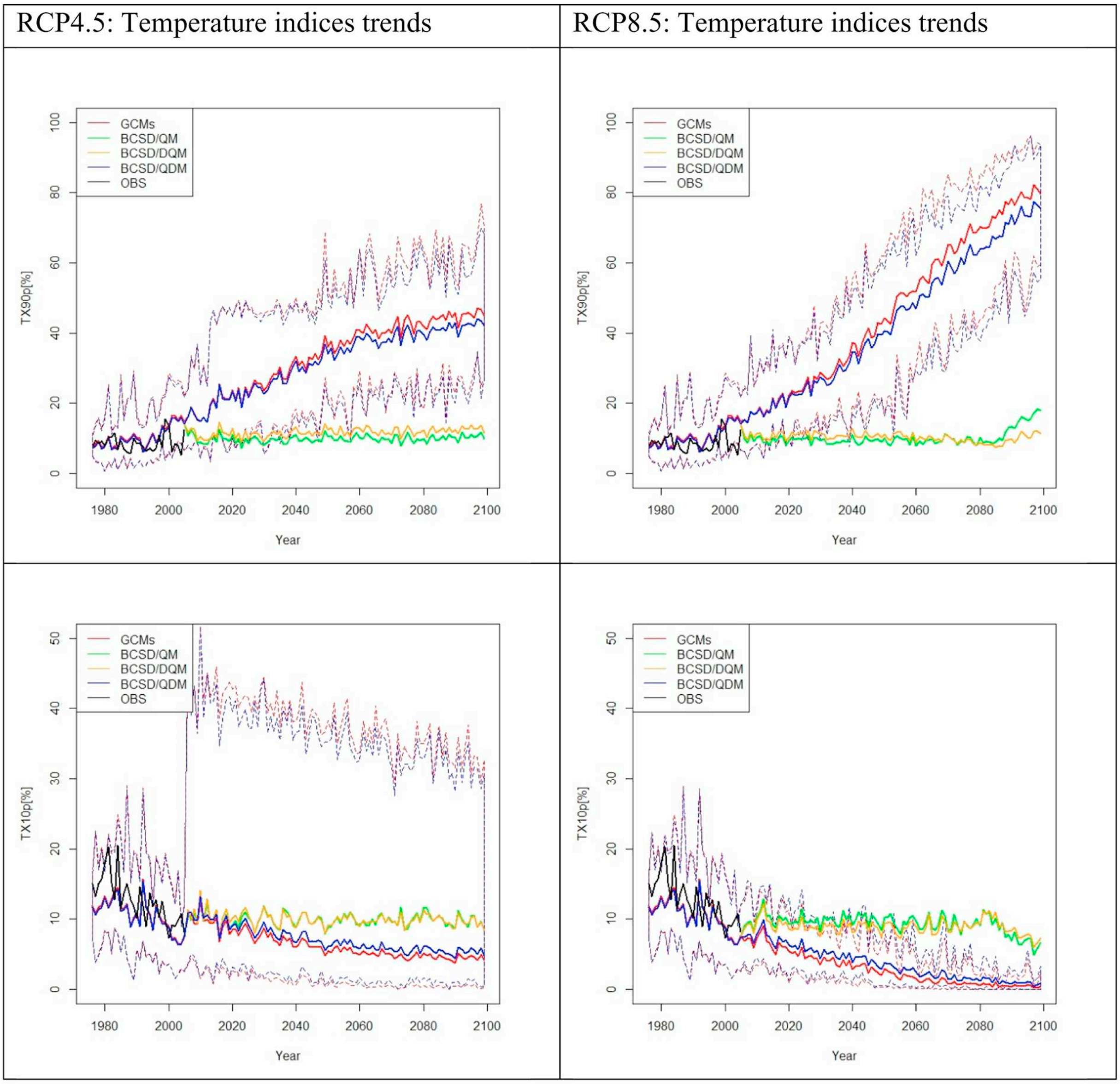



**Fig. 4.** Trends of temperature extremes (TX90p, TX10p, TN90p and TN10p) from 1976 to 2099, downscaled by three statistically downscaling methods of QM, DQM and QDM for RCP4.5 (left panel) and RCP8. 5 (right panel) over Pakistan.

similar to SP, however, during the first half, Sindh and Balochistan show the highest trends of warm spells.

The increase in the temperature extremes may pose socio-economic impacts and can lead to the occurrence of natural variability, heat waves, glacier melting, heavy rains and variation in hydrological cycle in different regions. Over northern areas of the country which host huge reservoirs of snow and glacier, may result in events like glacial lake outburst flood and snow/ice melt flooding. Furthermore, the increase in winter temperature may negatively affect the wheat production, which in turn can distress the overall food productivity and livelihoods of people. For reliable projections of climatic extremes finer resolution observation, climate models and improved downscaling techniques are needed which require hydrometeorological stations installation and proper monitoring.

### 3.2. Changes in precipitation extremes

Fig. 8 presents some of the observed and models ensemble trends for precipitation extremes from 1976 to 2005 over different regions of Pakistan. The overall observed trends for precipitation are in agreement with models' trends e.g. observed trend of PRCPTOT for Skardu and Peshawar corresponds with model trend as well as 1 day and 5 day precipitation trends for Balakot and Kotli are also similar. However, observed trend in total precipitation for DI Khan and R10mm for Gupis diverge from trend simulated by models. Also, it was observed that changes in precipitation are not as consistent as temperature changes and an overall decrease in total precipitation is observed in most part of Pakistan with increase (7–12%) in NP and KP (except Parachinar). For NP and KP, the total precipitation has shown more increase than any other precipitation indices, whilst the 5 day precipitation followed by 3 day precipitation has also shown a greater increase in NP. In KP R10 mm has shown less increasing trend than total precipitation where Peshawar and Kohat experienced the least R30mm and R20 mm respectively while in Parachinar, the precipitation indices have decreased reflecting dry conditions. However, mixed response to the precipitation indices was observed in SP where Bahawalnagar received maximum amount of total annual, 1 day and 5 day precipitation. With respect to MR which includes maximum rainfall receiving station, e.g., Murree, the total precipitation indices have decreased whereas an increase in extreme indices particularly 3-day precipitation has been observed.

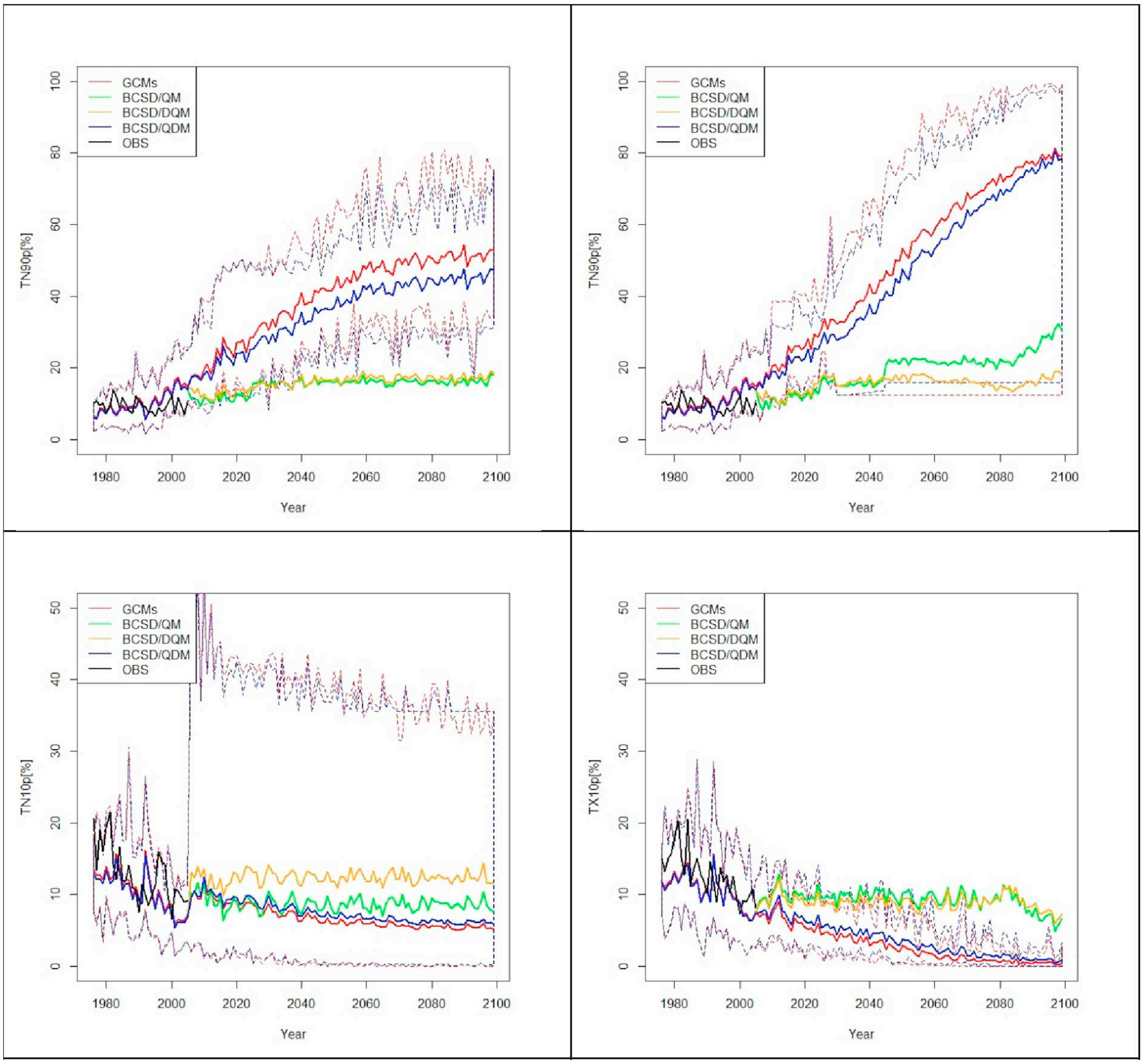



**Fig. 4.** (*continued*)

Similarly in Balakot, total precipitation trends have decreased whereas the extreme precipitation indices have increased among which the 1-day precipitation events are more frequent. Islamabad has also shown more increase in observed 1-day precipitation. The analysis of various observed precipitation indices over Sindh followed by Baluchistan indicates that precipitation events displayed no significant trend and are observed to decrease in 1976–2005, where Quetta and Karachi has the highest increase in consecutive dry days (CDD) which increases its vulnerability towards drought. This increase in vulnerability particularly in Karachi is linked with increase in population which is a major contributing factor of urbanization and may also aggravates the possibility of increase in frequency of heatwave across Sindh.

For the future projection of changes of precipitation extremes, the precipitation related indices are also divided into two groups in Fig. 10 where upper panel represents total amount of precipitation while lower panel depicts number of days. However, the changes in total precipitation in Pakistan under RCP4.5 and RCP8.5 are presented in Fig. 9. Fig. 10 shows the variability of indices between GCMs and relative absolute changes of precipitation extremes for RCP4.5 and RCP8.5. Generally, across whole Pakistan, the increase in annual total precipitation indices (PRCPTOT, R95pTOT and R99pTOT) is higher under RCP4.5 and RCP8.5 but changes in max 1-day precipitation (Rx1day) and max 5-day precipitation (Rx5day) are very less. However, RCP8.5 displays more increase as compare to RCP4.5. These results are consistent with Intergovernmental Panel on Climate Change (IPCC) (2013) which show increase in heavy precipitation extremes worldwide. Sillmann et al. (2013b) also show increase in PRCPTOT and R95p in most region around the world except Australia which is consistent to our results. The increase in extreme precipitation events (R95pTOT, R99pTOT, Rx1day and Rx5day) may induce more frequent and severe flood risk in densely populated areas and may cause a threat to life, property, food, agriculture, water resources and infrastructures. These results are also consistent with privoius studies (Ali et al., 2015; Wu et al., 2017), which shows the wetter climate in the future and increase of precipitation around 12–20% over Northern Pakistan. The increase in R95p and R99p is more in RCP8.5 than RCP4.5 which also consistent with Wu et al. (2017). The frequency of heavy precipitation or the proportion of total rainfall is increasing in 21st century especially on high mountains and monsoon regions which is in agreement with Intergovernmental Panel on Climate Change (IPCC) (2013) our observed data analyses on NP and KP also provide similar results. The analysis of consecutive dry days (CDD) show increasing trend while consecutive wet days (CWD) are decreasing. It is interesting to note that total precipitation is increasing and CWD is decreasing in all regions similar behavior is also seen in various station of SP for the observed data. Although there is an increase in the extreme precipitation but a

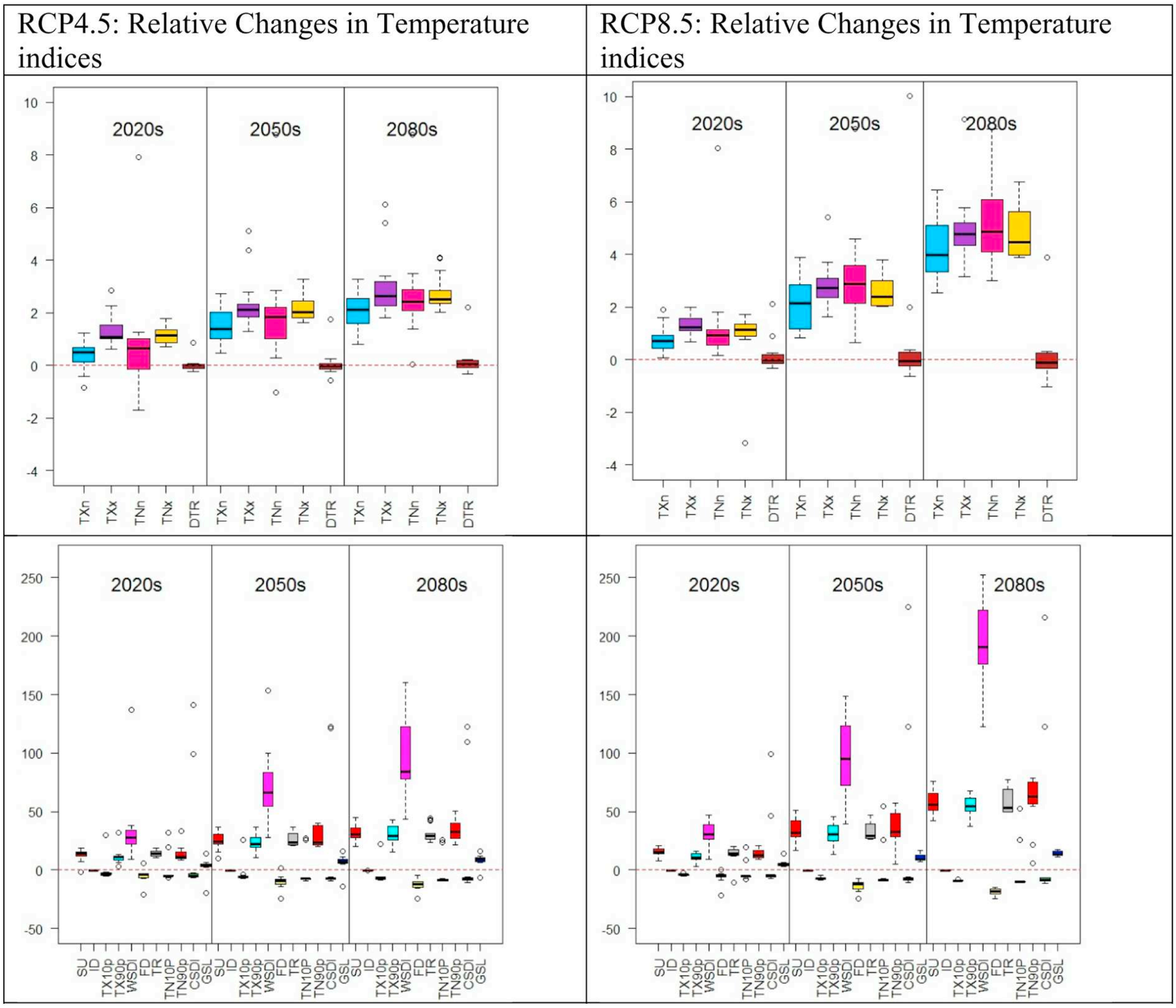



**Fig. 5.** Relative changes in maximum and minimum temperature-related extreme indices by projections from GCMs for RCP4.5 and RCP8.5 over Pakistan: the upper panel represents unit in Celsius (°C) and the lower pannel displays units of percentages and days.

decrease of CWD is not related to an increase in R95pTOT and R99pTOT. CDD is also increasing especially in the region of Sindh that is in consistency with the recent increase of worst drought observed in last decades and also indicates the prolongation of dry period across Pakistan. The northern areas (NP) has the lowest decrease in CWD during the 2020s. In MR, the CWD displays a decrease of 1.25 days. During 2050, SP displays the highest decrease in CWD while the increase in CDD with Sindh having the highest increase of 9 days. However, in MR the CDD are decreasing over all the three periods with more decrease during 2050. It is important to mention that the change in duration of CDD and CWD can exacerbate the flood and drought condition in the country, which is a complex process and needs more investigation on connection with other parameters of droughts and floods. This increase in CDD and decrease in CWD may also aggravate health risks, the concentration of pollutants in the air and the frequency of the forest fires. Simple precipitation density index (SDII) which is the ratio of PRCPTOT and CWD show a positive trend across Pakistan. Relative to Fig. 12, the analysis of precipitation indices on regional perspective depicts that the trend of SDII is highest in Sindh followed by Sothern Punjab, KP and others. For all the three periods (2020, 2050 and 2080) and among all the sub regions, Sindh possesses the highest increase in SDII of 2.4 days, 2.3 days and 2.5 days respectively. KP has the same increase in the number of SDII and CDD across all the three periods, i.e. 0.7 day in 2020, 1 day in 2050 and 1.25 days in 2080. The increasing trend of SDII is due to increase in annual total precipitation and decrease in CWD. In Northern Pakistan, the CDD shows more positive response during the 2050s which can lead to droughts in the region. While the overall trend of CDD is more in Sindh, Southern Punjab, Balochistan (sudden increase in 2080) and KP.

Precipitation trend (Fig. 11) in the provinces show an increase in Rx1day, Rx5day, R95pTOT and R99pTOT. However, the trend is not significant in Balochistan and Sindh; while the north region shows more increase as compare to the southern region. When comparing the precipitation extremes (PRCPTOT, R95pTOT, R99pTOT, Rx1 day and Rx5 day), MR indicates an increase of 120 mm in PRCPTOT and 122% and 100% increase in R95pTOT and R99PTOT respectively. Whereas Rx1day and Rx5day does not display larger increase i.e. 25 mm and 50 mm respectively. Over KP, the increase in PRCPTOT, R95pTOT, R99pTOT, Rx1 day and Rx5 day is observed to be 30 mm, 70%, 60%, 25 mm and 30 mm respectively. Among all the sub regions, Sindh have the least increasing trends in the precipitation indices. From the analysis it is observed that all the sub regions of Pakistan have the highest increasing trend of R95pTOT as compared to PRCPTOT, R99pTOT, Rx1 day and Rx5day.

A report from Asian Development Bank and Potsdam Institute show the increase of 50% more rainfall due to climate change in Asia, although countries like Pakistan and Afghanistan may experience a decline in rainfall by 20–50%. IPCC has forecasted fewer but intense rainy days, which means more flooding and less rainwater to percolate underground for aquifer recharge. Therefore, climate mitigation and

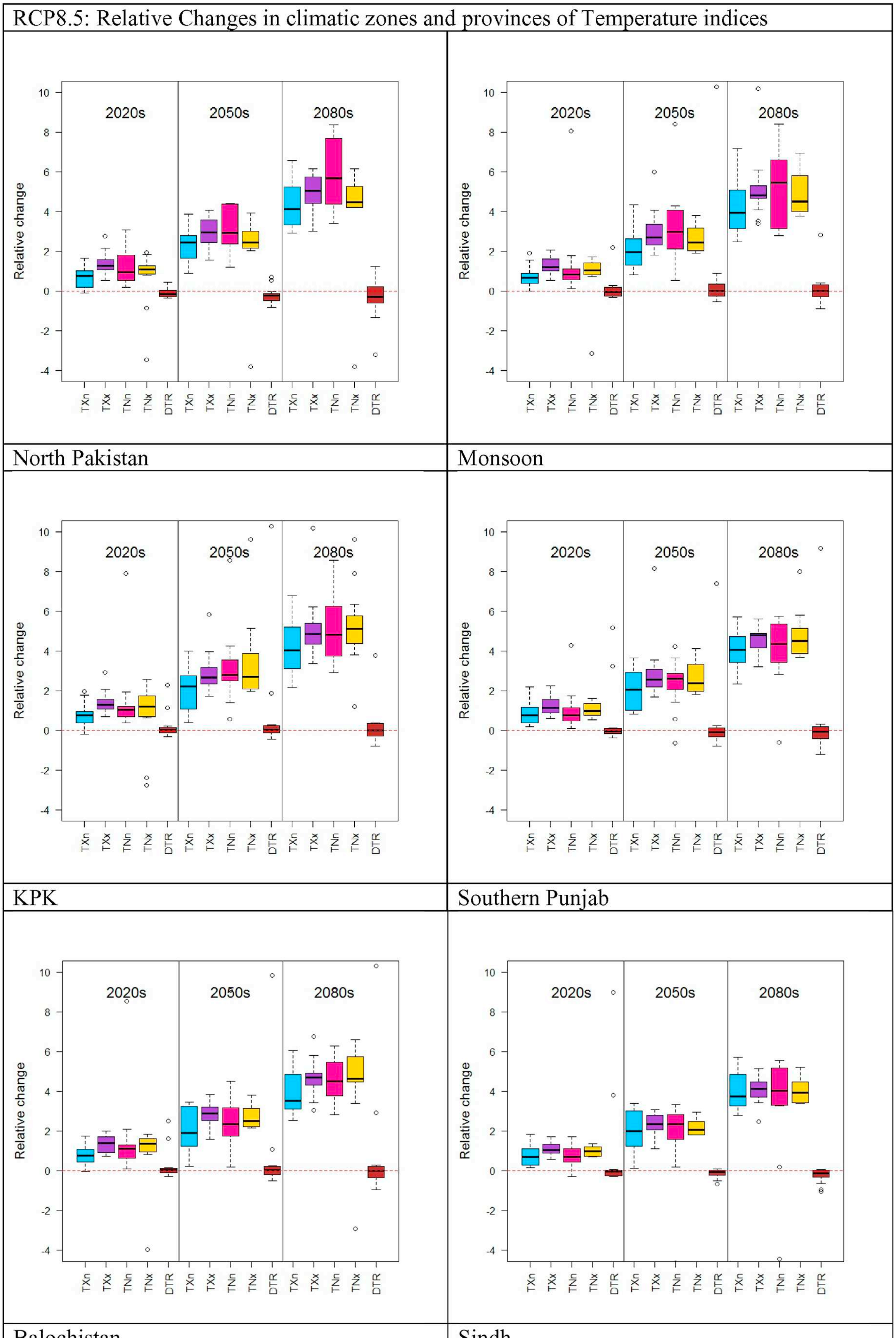



**Fig. 6.** Relative changes in maximum and minimum temperature-related extreme indices by projections from GCMs for RCP8.5 over sub regions of Pakistan. The units of indices are in Celsius °C.

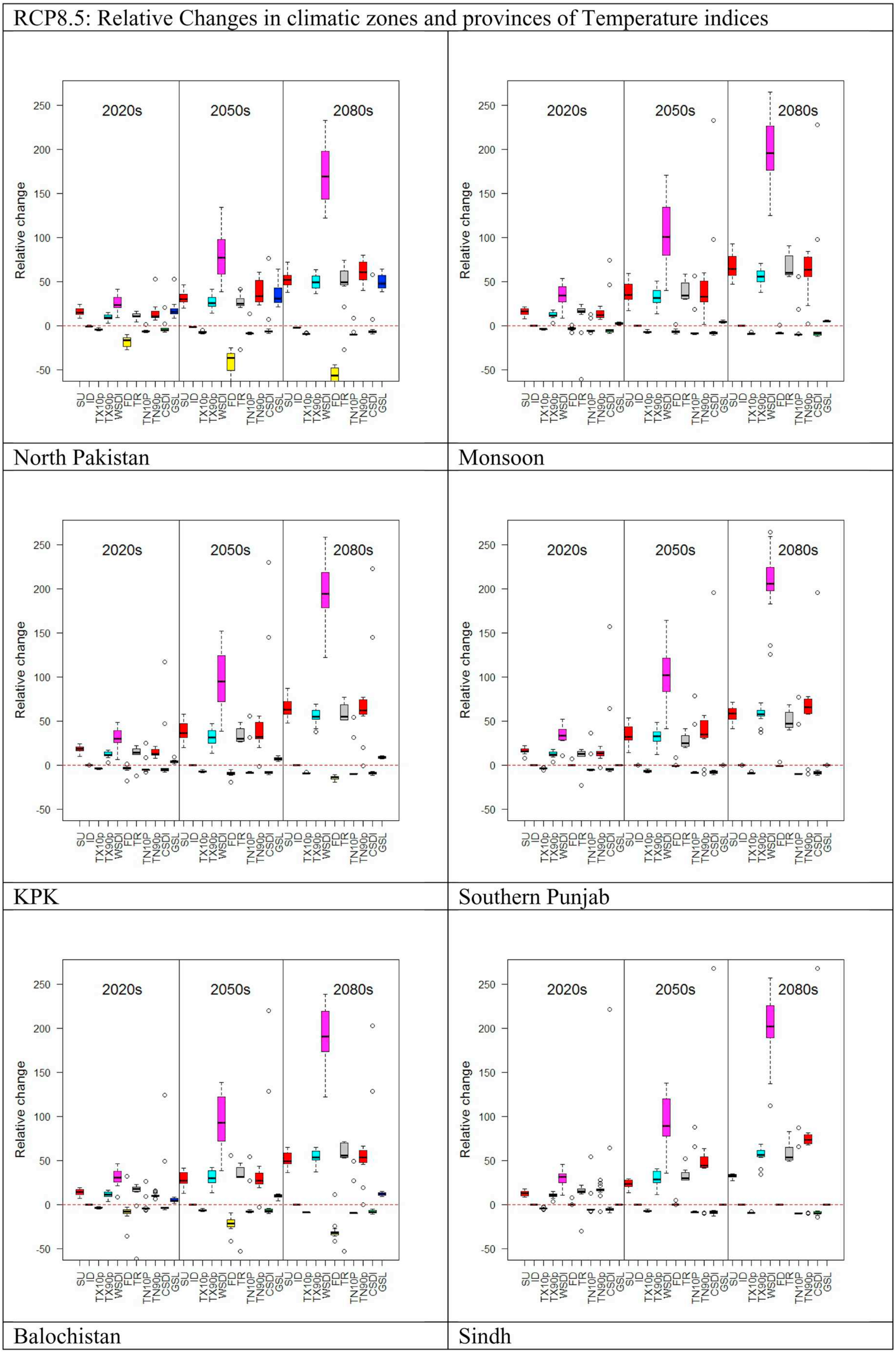



**Fig. 7.** Relative changes in maximum and minimum temperature-related extreme indices by projections from GCMs for RCP8.5 over sub regions of Pakistan. The units of indices are in percentages and days.


**Fig. 8.** Validation trends of time series of observed (blue) and models under ensemble mean (red) of precipitation extremes over different regions of Pakistan from 1976 to 2005. Straight lines represent linear regressions. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

adaptation efforts should also be mainstreamed into macro-level regional development strategies and micro-level project planning in all sectors. The results presented in this study provide complementary information for local decision-makers in policy making and infrastructure planning. Furthermore, the effect of changes in climate extremes on human health, agriculture and hydrology, which are closely

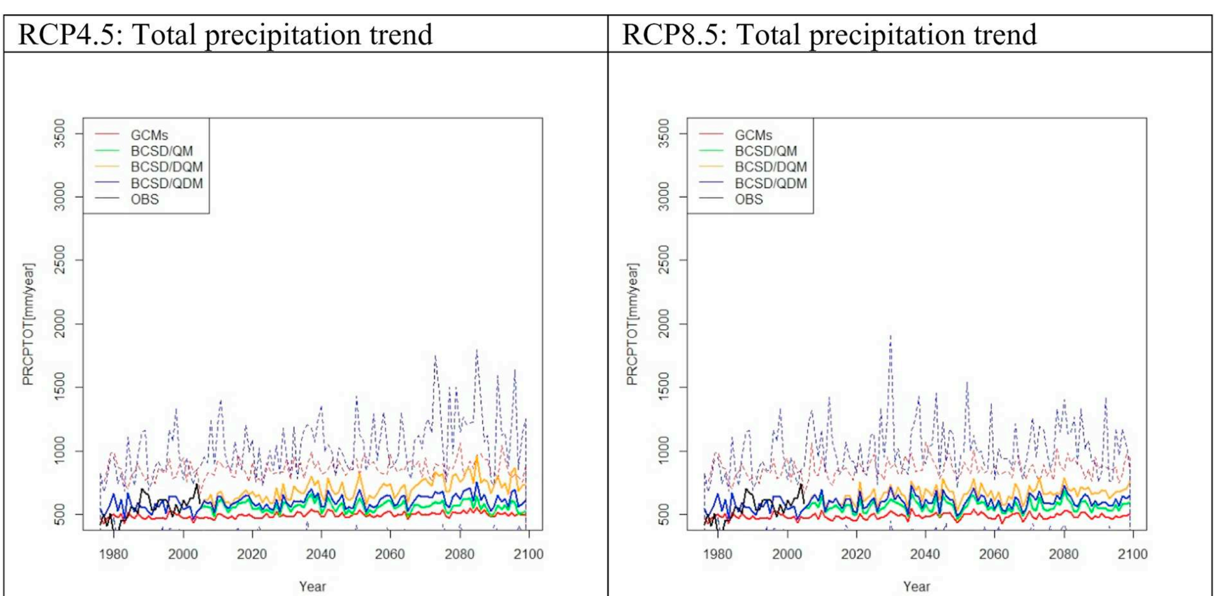



**Fig. 9.** Trends of total precipitation (PRCPTOT) from 1976 to 2099, downscaled by three statistically downscaling methods of QM, DQM and QDM for RCP4.5 (left panel) and RCP8. 5 (right panel) over Pakistan.

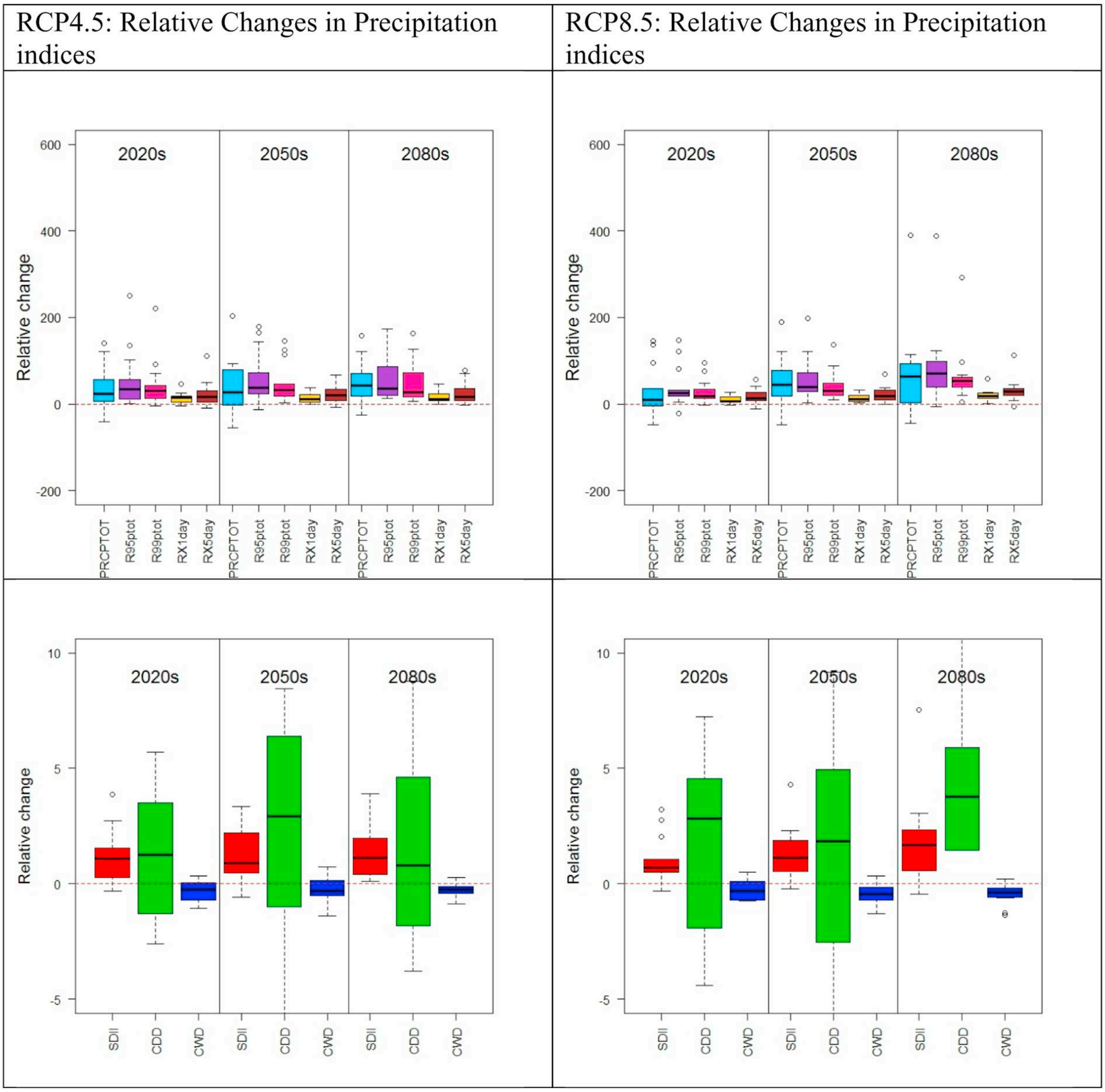



**Fig. 10.** Relative changes in precipitation-related extreme indices by projections from GCMs for RCP4.5 and RCP8.5 over Pakistan.

tied to societal development, should be further investigated in the future. Therefore, additional work considering the combined climate impacts will also be required to get more accurate projections in climate extremes.

## 4. Uncertainties in projections

The results of climate models projections are always susceptible to uncertainties mainly arising from models, anthropogenic/scenario forcing factors and natural variability. Out of all, major source of uncertainty arise from models which is mainly the result of inadequate understanding of geological processes and limitations in solving numerical schemes, parameterizations, and resolutions. Therefore, it is pertinent to enhance the understanding of regional and local uncertainties in projections by combining statistical approaches to extract regional interpretations of future projections from these models. For the assessment of uncertainty, we used Probability Density Functions (PDFs), Box whiskers plots and Signal to Noise Ratio (SNR).

PDFs in Fig. 13 show the probabilistic bimodal distribution of maximum temperature for NP which reveals the fact that maxima of maximum temperature reaches two times. The distributions of kurtosis and skewness for observed, baseline and future projections show agreement with each other. The shift in skewness for future periods of the entire distribution ranges from 0 °C to 40 °C in 1976–2005, 3 °C to 43 °C in 2020s, 3 °C to 45 °C in 2050s and 6 °C to 48 °C in 2080s. The negative skewness of all future periods show warmer climate that may increase the occurrence of temperature extreme in the future with more warm extremes and less cold extremes. Other PDFs also show more variations in RCP8.5 than RCP4.5. The similar analysis of PDFs is also used by Burhan (2018).

Box whiskers plots (Figs. 5–7 and Figs. 10–12) represent maximum temperature and precipitation. The temperature variation is more in northern part of Pakistan as compare to the southern part. RCP8.5 show more variations in values as compared to RCP45 for the future periods 2050s and 2080s. Moreover, the variation is high for precipitation and less for temperature.

The SNR values also show the uncertainty ranges of models (Shashikanth et al., 2014), we analyzed the performance of GCMs for the period of 1976–2005. In our results, the SNR is high in case of temperature whereas low in precipitation but overall greater than one

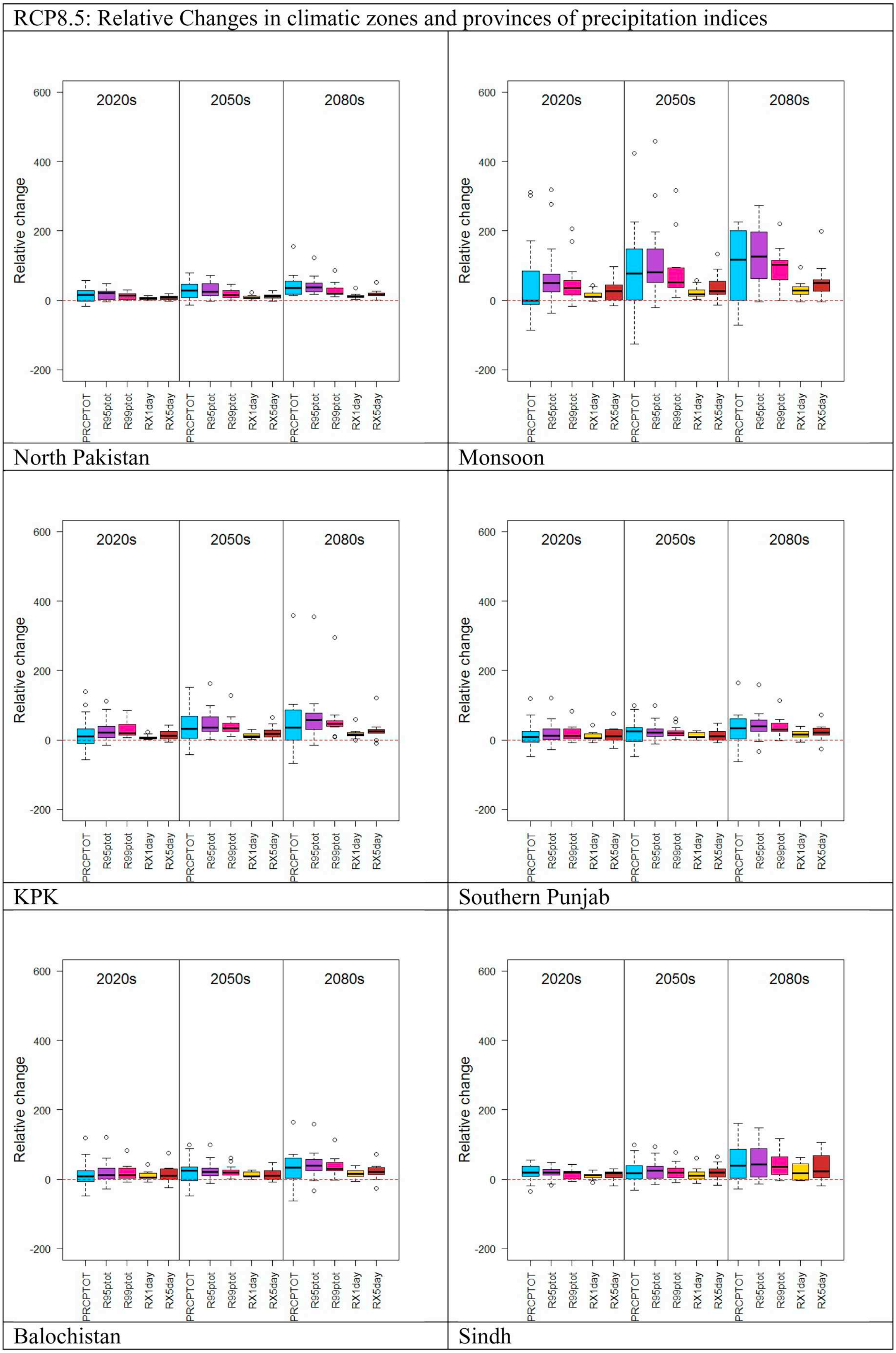



**Fig. 11.** Relative changes in precipitation-related extreme indices by projections from GCMs for RCP8.5 over sub regions of Pakistan.

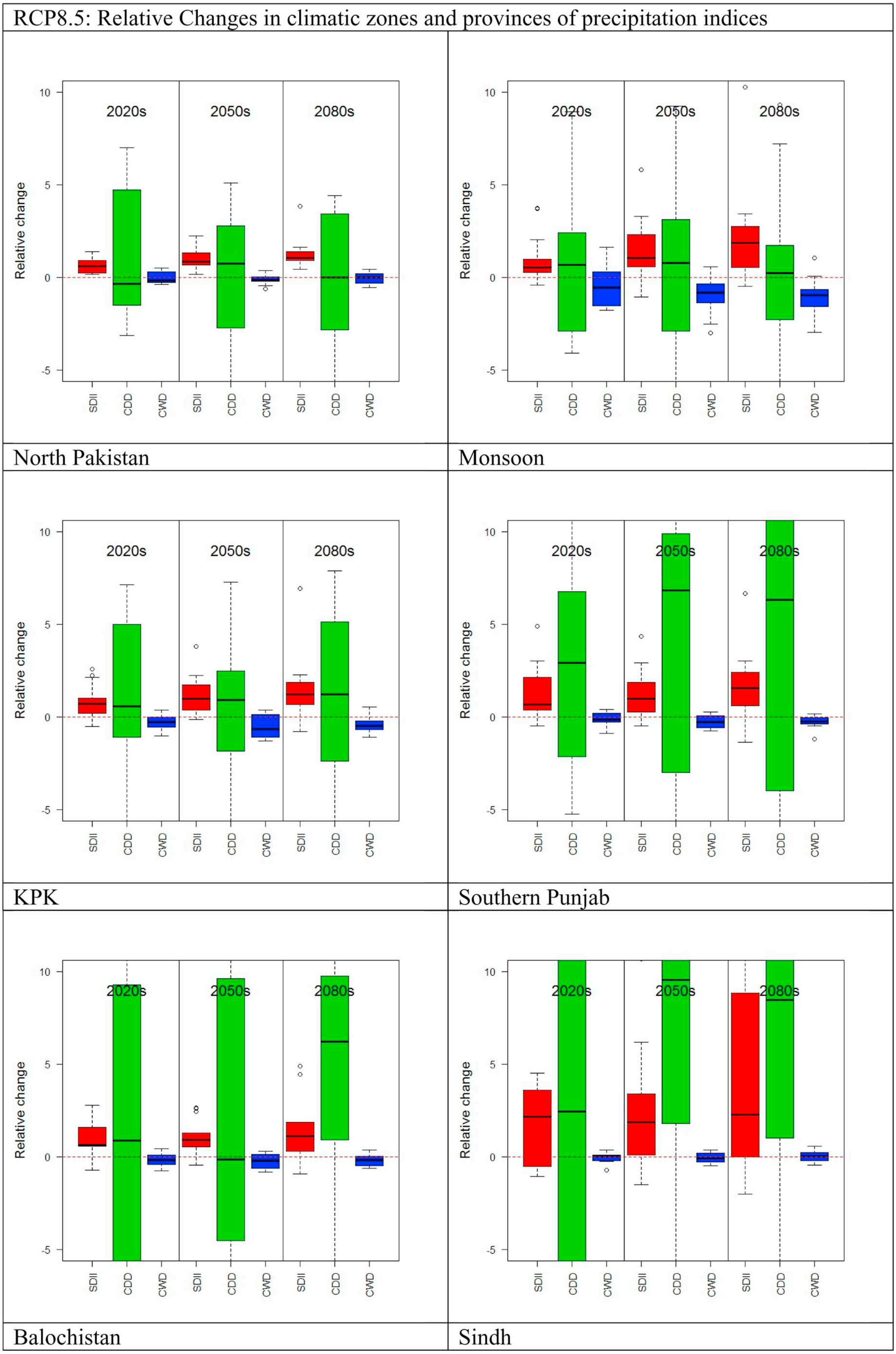



**Fig. 12.** Relative changes in precipitation-related extreme indices by projections from GCMs for RCP8.5 over sub regions of Pakistan.

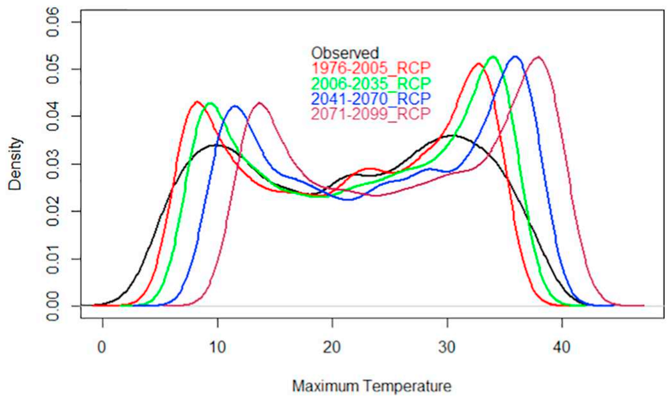



**Fig. 13.** Probability density functions of daily maximum temperature for the period of observed and baseline (1976–2005) and future (2006–2035, 2041–2070, 2071–2095) with RCP4.5 and RCP8.5.

(1) for both variables except for WSDI across various stations few being presented in Tables 3 and 4. Moreover, the observed SNR and multi-models ensemble show even higher value but ensemble value is not considered appropriate for SNR test. The relationship is linear for the higher value of SNR over all Pakistan. As low SNR indicates high uncertainty therefore when the SNR value is much greater than one (1), the signal is acceptable.

Although the current study provides detailed insight into climatic extreme events over Pakistan. However there are some limitations to this study. The study uses 14 CMIP5 GCMs with two future scenarios (RCP4.5 and RCP8.5). However, more GCMs and emission scenarios need to be evaluated with other statistical downscaling approaches with reliable process of selection of GCMs. The credibility of statistical downscaling models in non-stationary climate (Salvi et al., 2016; Dixon et al., 2016) needs further investigations and development of improved methods to assess non-stationary data in a better way. Over NP there exist few metrological stations only at lower elevations which represent the whole NP whereas there is more precipitation at high elevations. It is needed to add more stations after 50 km in plan areas and 10 km at high elevations to increase the confidence of policymakers in future projections of temperature and precipitation extremes in the region. In precipitation, there is more value spread than temperature yet the performance of the models is quite good for extremes except for a few. However, uncertainties also lie in observational data. These results indicate the climate change signal over Pakistan. However, for understanding of detail mechanism and causes of these extreme indices with large-scale forcings and seasonal cycle need to be investigated.

## 5. Conclusion and summary

In the past decades, the whole world has experienced more extreme events in the context of the frequency, magnitude and duration, which caused widespread causalities and economic losses. Therefore, it is imperative to acquire the information of future projections of these extremes to minimize their likely adverse impacts. This study provides an insight of observed (1996–2005) and future extreme events over Pakistan by using statistical downscaling/bias-correction methods (Quantile Mapping, Quantile Delta Mapping and Detrended Quantile Mapping). Out of all methods applied, QDM has proven to explicitly preserve long-term climate change signal in future from 1976 to 2095. Over the period from 1976 to 2005, the observed average temperature and maximum temperature has increased to 0.5 °C and 0.8 °C respectively. For the future projections under RCP4.5 and RCP8.5, CMIP5 models show the consistency in the increase in warm extremes (i.e TR, TX90, TN90p, TXx, TXn, TNx, TNn, SU and GSL) across Pakistan while cold extremes (i.e., FD, TN10p, TX10p, ID, and CSDI) are seen to be decreasing in terms of frequency and magnitude in overall Pakistan and sub-regions. Whereas across the whole country the temperature is increasing at a higher rate as compared to global mean and projected changes in daily minimum temperature (warm and cold nights) are more prominent than that for daily maximum temperature (warm and cold days) with respect to duration and frequency. Therefore, the rate of change in the minimum temperatures contribute more strongly to the overall increase of temperatures. Moreover, the highest increase in temperature is observed over north as compared to southern Pakistan. The results also depict a decrease in DTR with the highest increase in minimum temperatures in the north part of Pakistan. Summer days (SU) are increasing in all the regions with the highest increase of 70 days in KP and MR which provide an indication of the vulnerability of both regions. ID and FD are showing a decreasing trend over all parts while GSL depicts an increase in NP, monsoon and Baluchistan which indicates that the changes in the length of vegetation growing season has close relation to climate change. Cool nights (TN10p) and days (TX10p) show a decreasing trend while warm nights (TN90p) and days (TX90p) and tropical nights (TR) are increasing in all the sub-regions. However, the night temperature warming has greater contribution to overall warming process as compared to warming of day temperatures. The

**Table 3**
Signal to Noise Ratio (SNR) for temperature extremes of 14 GCMs (M1 = CanESM2, M2 = CCSM4, M3 = CESM1-CAM5, M4 = CMCC-CMS, M5 = CNRM-CM5, M6 = EC-EARTH, M7 = FGOALS-s2, M8 = GFDL-ESM2G, M9 = GFDL-ESM2M, M10 = inmcm4, M11 = MIROC-ESM-CHEM, M12 = MPI-ESM-LR, M13 = MPI-ESM-MR and M14 = NorESM1-M).

| Temperature SNR | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Index | Station | M1 | M2 | M3 | M4 | M5 | M6 | M7 | M8 | M9 | M10 | M11 | M12 | M13 | M14 | Models Mean | Observe |
| TN10p | Gupis | 2.03 | 1.87 | 2.32 | 1.99 | 1.96 | 1.87 | 1.80 | 2.05 | 1.78 | 2.54 | 2.38 | 2.74 | 2.29 | 1.87 | 3.68 | 1.14 |
| TN10p | Peshawar | 1.94 | 2.07 | 2.91 | 1.59 | 2.04 | 1.85 | 1.84 | 1.98 | 2.05 | 2.63 | 2.17 | 2.34 | 2.13 | 1.77 | 3.65 | 2.00 |
| TN10p | Karachi | 1.65 | 1.45 | 1.43 | 1.71 | 2.49 | 1.59 | 1.96 | 1.69 | 1.74 | 1.95 | 2.02 | 1.81 | 1.76 | 1.44 | 2.70 | 1.24 |
| TN90p | Lahore | 1.70 | 2.23 | 2.28 | 1.33 | 3.13 | 1.90 | 1.61 | 1.83 | 1.94 | 3.00 | 1.68 | 1.82 | 1.35 | 1.53 | 3.08 | 1.36 |
| TN90p | Quetta | 1.84 | 1.56 | 2.10 | 1.31 | 2.69 | 1.51 | 1.70 | 1.93 | 1.94 | 2.40 | 1.69 | 2.08 | 1.51 | 1.67 | 2.90 | 2.09 |
| TX10p | Islamabad | 1.76 | 2.17 | 2.50 | 1.70 | 2.50 | 1.96 | 1.86 | 2.64 | 2.11 | 2.37 | 2.30 | 2.43 | 2.15 | 1.77 | 4.47 | 2.59 |
| TX10p | Karachi | 1.84 | 2.27 | 1.86 | 2.25 | 2.46 | 1.81 | 2.45 | 1.91 | 2.03 | 2.26 | 2.18 | 2.48 | 2.18 | 2.10 | 3.97 | 1.96 |
| TX90p | Gilgit | 1.56 | 1.82 | 1.69 | 1.55 | 1.12 | 1.77 | 2.34 | 1.75 | 1.45 | 2.17 | 2.42 | 1.57 | 1.59 | 1.53 | 3.42 | 1.59 |
| TX90p | Parachinar | 1.49 | 2.11 | 1.68 | 1.69 | 1.57 | 1.50 | 2.53 | 1.92 | 1.84 | 2.14 | 2.82 | 1.77 | 1.55 | 1.69 | 3.50 | 1.82 |
| Su | Gilgit | 10.90 | 11.69 | 11.21 | 10.67 | 10.98 | 9.27 | 13.70 | 12.57 | 10.15 | 14.28 | 11.71 | 9.93 | 12.93 | 11.49 | 28.98 | 13.33 |
| Su | Lahore | 23.57 | 18.83 | 20.70 | 20.19 | 25.96 | 16.59 | 25.46 | 23.03 | 20.54 | 23.52 | 22.00 | 18.63 | 19.18 | 19.34 | 54.58 | 20.10 |
| Su | Lahore | 23.57 | 18.83 | 20.70 | 20.19 | 25.96 | 16.59 | 25.46 | 23.03 | 20.54 | 23.52 | 22.00 | 18.63 | 19.18 | 19.34 | 54.58 | 20.10 |
| Su | Quetta | 15.27 | 15.88 | 16.07 | 15.88 | 16.04 | 12.47 | 18.95 | 18.25 | 15.11 | 14.89 | 18.32 | 13.76 | 16.45 | 16.34 | 35.95 | 15.26 |
| Wsdi | Gilgit | 0.83 | 0.87 | 0.84 | 0.87 | 0.60 | 0.86 | 1.07 | 0.93 | 0.80 | 0.92 | 0.98 | 0.86 | 0.70 | 0.73 | 2.16 | 0.70 |
| Wsdi | Parachinar | 0.80 | 0.71 | 0.93 | 0.92 | 0.95 | 0.81 | 0.80 | 0.96 | 0.83 | 0.88 | 0.72 | 0.77 | 0.72 | 0.92 | 1.97 | 0.63 |
| Wsdi | Balakot | 0.71 | 0.71 | 0.91 | 0.95 | 0.83 | 0.70 | 0.95 | 1.01 | 0.88 | 1.01 | 0.79 | 0.72 | 0.71 | 0.80 | 1.93 | 0.73 |

**Table 4**
Signal to Noise Ratio (SNR) for precipitation extremes of 14 GCMs (M1 = CanESM2, M2 = CCSM4, M3 = CESM1-CAM5, M4 = CMCC-CMS, M5 = CNRM-CM5, M6 = EC-EARTH, M7 = FGOALS-s2, M8 = GFDL-ESM2G, M9 = GFDL-ESM2M, M10 = inmcm4, M11 = MIROC-ESM-CHEM, M12 = MPI-ESM-LR, M13 = MPI-ESM-MR and M14 = NorESM1-M).

| Precipitation SNR | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Index | Station | M1 | M2 | M3 | M4 | M5 | M6 | M7 | M8 | M9 | M10 | M11 | M12 | M13 | M14 | Models Mean | Observe |
| PRCPTOT | Skardu | 2.08 | 2.49 | 2.49 | 2.27 | 2.95 | 2.80 | 2.46 | 2.73 | 2.07 | 3.03 | 3.09 | 2.68 | 2.67 | 2.26 | 9.04 | 2.17 |
| PRCPTOT | Peshawar | 1.80 | 2.52 | 2.47 | 1.80 | 3.67 | 3.07 | 1.71 | 2.76 | 1.73 | 2.34 | 2.40 | 2.33 | 2.96 | 2.67 | 7.94 | 2.96 |
| PRCPTOT | DI khan | 2.17 | 2.98 | 2.38 | 2.39 | 4.08 | 3.75 | 2.08 | 3.10 | 1.98 | 2.51 | 3.03 | 2.88 | 3.09 | 3.43 | 9.24 | 3.84 |
| R10mm | Gupis | 1.86 | 1.94 | 2.00 | 1.80 | 2.17 | 2.03 | 1.50 | 1.97 | 1.45 | 1.87 | 1.85 | 1.96 | 2.14 | 1.67 | 6.41 | 1.25 |
| R10mm | Muzaffarabad | 2.85 | 4.54 | 4.73 | 3.23 | 7.13 | 4.98 | 2.84 | 4.05 | 3.03 | 3.65 | 4.96 | 5.28 | 3.88 | 4.23 | 13.00 | 6.53 |
| R20mm | Peshawar | 1.46 | 1.71 | 1.89 | 1.46 | 2.04 | 2.52 | 1.32 | 2.25 | 1.31 | 1.77 | 1.73 | 1.58 | 2.38 | 2.09 | 5.69 | 2.24 |
| Rx1day | Balakot | 2.05 | 2.21 | 2.51 | 2.31 | 2.61 | 2.34 | 2.50 | 2.30 | 2.18 | 2.24 | 2.14 | 2.34 | 2.53 | 2.15 | 9.44 | 2.61 |
| Rx5day | Kotli | 2.25 | 2.83 | 3.12 | 2.67 | 2.80 | 1.91 | 2.22 | 2.69 | 2.61 | 2.21 | 2.77 | 2.67 | 2.53 | 2.60 | 11.50 | 2.61 |

results over Pakistan are in agreement with global studies which indicate that anthropogenic activities would cause fewer cold extremes and more warm extremes in 21st century. These analysis of climatic extremes are also consistent with. Also the changes in temperature extremes, e.g., TXn, TNn and TN10p are stronger in North Pakistan (high-latitude and high-altitude) and especially in winter which can be due to the ice and snow albedo response.

This increased warming will result in more rainfall events and can also intensify the hydrological cycles in most of the parts of Pakistan that may lead to flooding and drought at the regional scale. However, the lower agreement is observed in case of precipitation extremes among CMIP5 models than temperature extremes. The simple daily intensity of precipitation (SDII), extremely wet days (R99p) and very wet days (R95p) is increasing and indicating climate change response. Additionally, the increase in consecutive dry days (CDD) and decrease in consecutive wet days (CWD) present uniform responses to the warming. In NP, KP and MR, there is a significant increase in precipitation days of very wet days (R95p), five-day precipitation (Rx5day) and heavy precipitation. The results of future projections of precipitation extremes also suggest a consistent increase in extreme precipitation contribution to total annual precipitation (except for a slightly decreasing trend in Sindh which can contribute to drought conditions). Although there is an increase in the extreme precipitation but a decrease of CWD in all regions is not related to an increase in R95pTOT and R99pTOT.

The increase in SU and decrease in ID over NP is threatening in terms of snow and glacier melting, glacier lake outburst and flooding. Most of these extreme indices specially TXx, TX90p, CDD and TX5days can effect health, agriculture, food security, water resource and flooding in multiple ways, hence, requires further analysis in details. Moreover, the increase of extreme rainfall events if combined with monsoon rain can also pose serious risk of floods in regions. In NP, KP and MR, the agricultural productivity can be effected due to high increase in the minimum temperature. Also, the increase of warm days, SU and max temperature over Sindh can expose the region to heatwaves, drought and water stress. As climatic extremes can have devastating impacts on livelihood of people, agriculture, economy and society in the future, the current study provides complementary information to decision makers that can contribute in effective policy making and infrastructure planning. Also, the improvement of early warning and emergency response capacities for extreme climate events is needed. Apart from this, it is pertinent to enhance the public awareness of these climatic extremes risk through media, social network and educational activities. In this regard, further studies are highly recommended to explore the climatic extreme in more details of finer scale (higher-resolution models) with sophisticated knowledge of observation.

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